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Retrieving leaf area index from SPOT4 satellite data

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Abstract A research project was conducted as collaboration between the National Authority for Remote Sensing and Space Sciences (NARSS) in Egypt and the Institute of Remote Sensing Applications (IRSA), Chinese Academy of Sciences. The objective of this study is to generate normalized difference vegetation index (NDVI)–leaf area index (LAI) statistical inversion models for three rice varieties planted in Egypt (Giza-178, Sakha-102, and Sakha-104) using the data of two rice growing seasons. Field observations were carried out to collect LAI field measurements during 2008 and 2009 rice seasons. The SPOT4 satellite data acquired in rice season of 2008 and 2009 conjunction with field observations dates were used to calculate the vegetation indices values. Statistical analyses were performed to confirm the assumptions of inversion modeling for plant variables and to get reliable models that fit the inversion relationship between LAI and NDVI. The inversion process resulted in three NDVI–LAI models adequate to predict LAI with 95% confidence for the three different rice varieties. The accuracy of the generated models ranged between 50% in the case of Sakha-104 and 82% in the case of Giza-178. LAI maps were produced from NDVI imageries based on the generated models.

1. Introduction

Leaf area index (LAI) is defined, as the total one-sided leaf area per unit ground area. It is one of the most important biophysical parameters characterizing a canopy. The temporal and spatial distributions of LAI are often needed in global circulation models to compute energy and water fluxes. Since LAI directly quantifies the plant canopy structure, it is highly related to a variety of canopy processes, such as evapotranspiration, light interception, photosynthesis, respiration and leaf litter fall. Remotely sensed estimation LAI would greatly assist the application of LAI as an input for photosynthesis, crop growth simulation models, evapotranspiration, estimation of net primary productivity and vegetation/biosphere functioning models for large areas, at cost effective way.

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The most commonly used vegetation index in remotely-sensed vegetation studies is the normalized difference vegetation index (NDVI). It is defined as the model for converting satellite-based measurements into surface greenness and vigor of vegetation types. NDVI has the advantage that no auxiliary information is required (Bach, 1998). A number of techniques for space borne remote sensing data have been developed/tested, ranging from regression models to canopy reflectance model inversions, which include: (a) statistical models that relate LAI to band radiance (Badhwar et al., 1986) or develop LAI–vegetation index relation (Chen and Cihlar, 1996); (b) biophysical models (Price, 1993) and (c) inversion of canopy reflectance using numerical model or LUT based model (Gao and Lesht, 1997; Qiu et al., 1998; Knyazikhin et al., 1998). Myneni et al. (1997) developed a simple approach for estimating global LAI from atmospherically corrected NDVI using NOAA-AVHRR data. One- or three-dimensional radiative transfer models were used to derive land cover-specific NDVI–LAI relations where coefficients are determined by vegetation type and soil. Chen et al. (2002) have described relations using NOAA-AVHRR simple NIR/red ratio (SR). These equations are vegetation type dependent and are being used to generate Canada wide 1 km LAI maps every 10/11 days. In case of another high receptivity coarse resolution sensor, vegetation on board SPOT satellite, use of SWIR channel is made to compute a new vegetation index, namely Reduced Simple Ratio (RSR). RSR reduces between vegetation and understory/background effects, thus making possible the use of simplified equations for retrieval of LAI. Rastogi et al. (2000) tested Price model (Price, 1993) on farmers fields using the Indian Remote Sensing Satellite (IRS) LISS-III data and estimated attenuation coefficients. The root mean square error (RMSE) between RS estimates and ground measured LAI ranged between 0.78 and 0.87 when LAI was in the range of 1–4, while for higher LAI range (4–6), the RMSE varied from 1.25 to 1.5 in two sites. Such errors can severely reduce utility of a model using field-level LAI as input.

The main objective of this study is to generate statistical empirical model to retrieve LAI from SPOT4 spectral reflectance data represented by NDVI under Egyptian local conditions, which help as crop monitoring system and crop yield prediction.

2. Study area

The study area is located in Sakha experimental farm, Kafr El-Sheikh governorate, Egypt. It consists of 27 feddans cultivated with three rice varieties (Sakha-102), (Sakha-104) and (Giza-178). The area was located between 31°6′40″ and 31°6′0″ North and 30°54′30″ and 30°55′60″ East. The data given by Sakha research station indicate that the mean maximum temperature varies from 19.2 °C in January to 34.0 °C in July while the mean minimum temperature varies between 6.1 °C in January and 19.3 °C in August. The mean annual temperature ranges between 12 °C and 27 °C. The precipitation in the study area is only around 50 mm. As crop growth is only possible with irrigation, knowledge of water losses is essential for planning water application rates. Concerning rice season, daily climatic data for the study area during rice growing season (April to August) were collected from Daily Weather Observation Unit of the Agricultural Research Center. The highest maximum and minimum air temperatures were recorded during the month of August, while the lowest one was recorded during the month of April. El-Nahal et al. (1977), reported that, the alluvial soils of the study area were formed from Nile sediments, which have accumulated to a considerable thickness as a consequence of the sedimentation procedure of the river having four thousands of years annually over flowed its banks and deposited its load of the suspended materials on its flood plain and Delta. The thickness of these deposits varies partly to the surface topography of the sedimentation bed, and partly to the river having, from time to time, changing its path, eroding the sand that had been deposited from water. Based on the morphological studies and laboratory analyses, the soil of the study area could be classified into the following. (I) Soil of the recent Nile alluvium. These soils represent the majority of the Delta. They are characterized by their dark to very dark brown color and their light to heavy clay texture with minor variations through the whole profiles. The clay content is generally above 40% in the southern part and increases gradually to the north reaching almost 70%. The same pattern occurs laterally on both sides of the river branches, where texture is light close to the stream sandy loam to clay loam and gets finer with increasing distance from the banks. (II) Soils of the marine alluvium. They are characterized by heavy clay texture and the Nile sediments are often mixed with marine deposits, moreover, the alluvial and marine alluvial soils are characterized by the presence of mottling in deep subsoil layers close to the ground water zone especially in the northern part of the Delta. The soil structure is mainly coarse to medium prismatic or blocky. The soils are generally compacted and very hard when dry, and becomes sticky upon wetness. Compactness increases with depth to a marked degree in the northern part due to the high content of clay and to the increase of sodium and magnesium salts in the subsoil near the ground water zone. Calcium carbonate content ranged from 1% to 3%, gradually decreasing with depth. The location of the study area and the field observation are shown in Fig. 1.

3. Materials and methods

3.1. Satellite data

Two SPOT images acquired in August 3rd 2008 and August 23rd 2009 were combined by the bands 2, 3 and 4 to be used in the current study. Each dataset were displayed and visually examined for the probable signature degradation contained. Since the data were radiometrically corrected, no significant noises were found in either of the dataset corresponding to the study areas while examining enhanced images visually. Geometric transformation was carried out using selected ground control points (GCPs) in order to give the images the integrity of the maps, enable the manipulation of the images with other geographic database and to map the original satellite data to a geometrically correct output grid. SPOT data were geometrically projected to (lat/long) projection system using GCPs whose real coordinations were obtained from available 1:50,000 scale digital topographic map. The root mean square (RMS) error below half pixel (0.5) was accepted with the first-degree polynomial and nearest neighbor resembling algorithm technique. For each rice field under investigation, the actual NDVI values were calculated from SPOT band

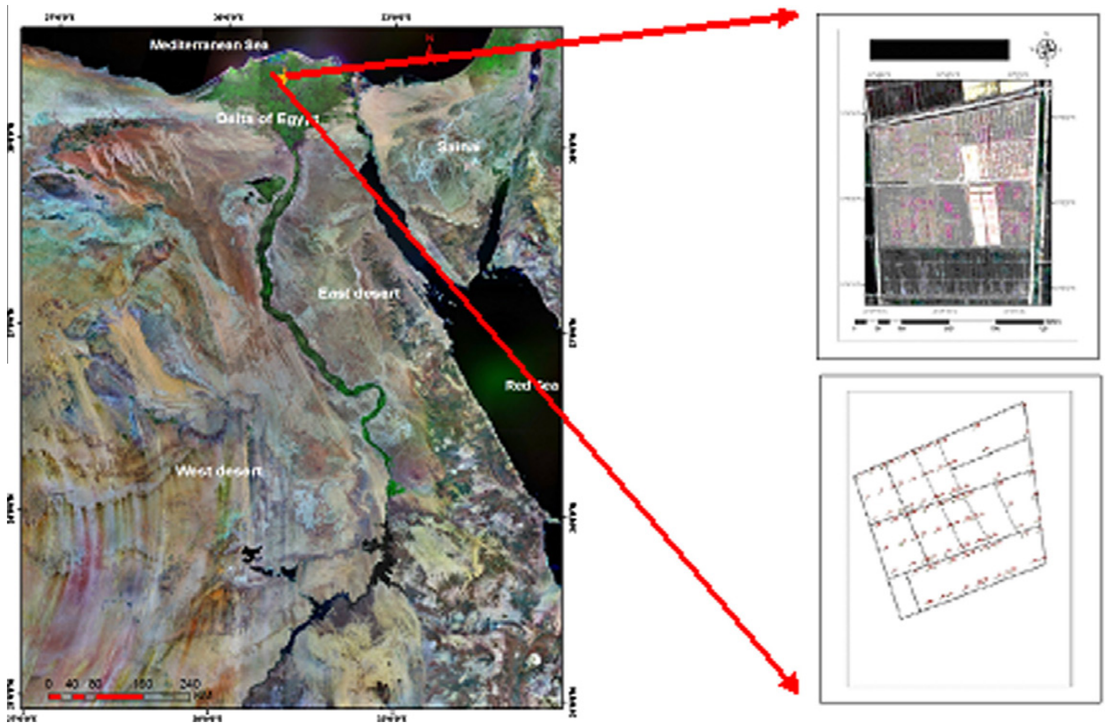

Figure 1 Location map of the study area and field check points.

3 (red) and band 4 (near infrared) to be used in the modeling process.

3.2. Field observations

Field observations were carried out in Sakha experimental fields during the two rice seasons of 2008 and 2009 at different growing stages of rice crop. At the beginning, the study area was divided into different parcels based on grid system decided by the research team. Ninety-four checkpoints were chosen as the main dataset for the modelling process. The checkpoints were divided into three parts according to the rice varieties as: 22 points from (Sakha-102), 36 points from (Giza-178) and 36 points from (Sakha-104). These points represent most possible variations in soil conditions and agricultural practices which may occur within the experimental fields. LAI-2000 Plant Canopy Analyzer was used in all field observations to measure LAI for each point. This device calculates LAI and other canopy structure attributes from radiation measurements made with a (fish-eye) optical sensor (148° field of view). Measurements were made above and below the canopy to determine canopy light interception at 5°, from which LAI is computed using a model of radiative transfer in vegetative canopy. After collecting the above and below canopy measurements, the control unit performs all calculations and the results are available for immediate on-site-inspection. All measurements of the two seasons were combined in one dataset and the calculations process includes:

– LAI for broad canopies, or foliage density for isolated canopies.
– Mean foliage inclination.
– The fraction of the sky visible from beneath the canopy.

3.3. Statistical analysis

The LAI data of the obtained samples were subjected to some statistical analysis and techniques including outlier's detection, and normality tests, homogeneity of variance tests, analyses of variance, and regression statistical relationship.

3.4. Outliers

Outlier is a value in a statistical sample which does not fit a pattern that describes most other data points specifically a value that lies 1.5 IQR beyond the upper or lower quartile (Barnett et al., 1994). Many statistical techniques are sensitive to the presence of outliers and may be distorted by a single grossly inaccurate data point (Motulsky and Brown, 2006). The maximum normalized residual test was applied to test LAI data for outlier's existence (Iglewicz and Hoaglin, 1993) where the hypothesis of no outliers is rejected two-sided test if

$$G = \frac{(N - K_i)}{\sqrt{N}} \sqrt{\frac{t^2_{(\alpha/(2N)N-2)}}{N - 2 + t^2_{(\alpha/(2N)N-2)}}} \qquad (1)$$

where G expresses the test of the maximum normalized residual and $t^2_{(\alpha/(2N)N-2)}$ denoting the critical value of the t-distribution with $(N-2)/2$ degree of freedom and a significant level of $\alpha/(2N)$. The LAI data were tested for normality as mentioned above hence this test assumes normality of data.

3.5. Normality tests

LAI data were tested for deviation from Gaussian distribution using two normality tests which are Kolmogorov–Smirnov

(KS) test with Lilliefors significance correction (Chakravarti et al., 1967) and Shapiro–Wilk test (Shapiro and Wilk, 1965; Pearson and Hartley, 1972). The Kolmogorov–Smirnov test statistics is defined as:

$$D = \max_{1 \leqslant i \leqslant N} \left(F\left(Y_i - \frac{i-1}{N}, \frac{i}{N} - F(Y_i) \right) \right) \quad (2)$$

where D expresses the Kolmogorov–Smirnov test statistics and F is the theoretical cumulative distribution of the distribution being tested. Normal Q–Q models were plotted for diagnosing differences between the probability distribution from which the random samples have been taken. For Q–Q model requirements, Blom's formula (Blom, 1958) was used for proportion estimation and the mean was used as the rank assigned to ties with no data transformation.

3.6. Homogeneity of variance

Levene's test (Levene, 1960) was used to assess the equality and homogeneity of variance (homoschedasticity) in the three rice verities LAI data. Also the other variants of Levene's test (Brown and Forsythe, 1974) were performed for robust estimations. The assumption of the tests that the null hypothesis is that the population variances are equal where:

$$w = \frac{(N-K_i)\sum_{i=1}^{k} N_i(\overline{Z_i} - \bar{Z})^2}{(K-1)\sum_{j=1}^{k}\sum_{i=1}^{N_i}(\overline{Z_{ij}} - \overline{Z_i})^2} \quad (3)$$

where w expresses the Levene's test statistics. Given a variable Y with sample of size N divided into k subgroups, where N_i is the sample size of the ith subgroup, and Z is equal to $|Y_{ij} - Y_i|$ where Y_i is the mean of the ith subgroup.

Analysis of variance: one-way analysis of variance (ANOVA) combined with linear trend test was performed on LAI data to test if that the random sampling would result in means as far apart from one another or more so as observed in LAI data and if that the random sampling would result in a slope as far from zero or further than obtained from LAI data.

3.7. Regression analyses

Weighted least squares (WLS) regression model compensates for violation of the homogeneity of variance assumption by weighting cases differentially in estimating the regression coefficients. The standard errors are smaller and the weighted sum of squared residuals is:

$$S = \sum_{i=1}^{n} W_{ii} r_i^2, \quad W_{ii} = \frac{1}{\sigma_i^2} \quad (4)$$

While S is the weighted sum of squared residuals. The gradient equations for the sum of squares are:

$$-2\sum_i W_{ii} \frac{\partial f(x_i, \beta)}{\partial \beta_j} r_i = 0, \quad j = 1, \ldots, n \quad (5)$$

Which, in a linear least squares system give the modified normal equations:

$$\sum_{i=1}^{n}\sum_{k=1}^{m} X_{ij} W_{ii} X_{ik} \widehat{\beta_k} = \sum_{i=1}^{n} X_{ij} W_{ii} y_i, \quad j = 1, \ldots, m \quad (6)$$

For the purpose of testing hypotheses about the values of model parameters, an Ordinary Least Square Regression Model (OLSRM) was performed between LAI and NDVI for the three rice varieties. Weighted Least Square Regression Model (WLSRM) was performed to correct the heteroscedasticity in the residuals in order to obtain valid estimates in further analyses. A range of weight transformations were tested and a range of power values were examined for a more tuned model. For each of the power values, a weighted least squares model was fitted and the value that gave the best fit (largest log-likelihood) was chosen.

4. Results and discussion

4.1. Outliers

As many statistical techniques are sensitive to the presence of outliers, a maximum normalized residual test was applied. The test showed no outliers that lie 1.5 beyond the upper or lower quartile of the LAI data with a significance level of 0.05 (two tailed) and 2.99 critical value of Z. The LAI data of the obtained samples were subjected to the descriptive statistical analyses (measures of central tendency, measures of dispersion, and measures of shape) to fulfill the assumption normality.

4.2. Descriptive statistics

The values of standard variation show a high biological variation and, on average, these values will not change predictably by acquiring more data as the standard deviation value quantifies the scatter of LAI data around its mean and the scatter of data will not change by increasing the size of the LAI samples. Also the frequency distribution indicated that the distribution of the LAI data follows nearly a bell-shaped Gaussian distribution as about 61.11% of data lie within one standard deviation of the mean.

4.3. Normality tests

The results of Kolmogorov–Smirnov (KS) test showed that, KS statistics is 0.073 for Giza-178, 0.129 for Sakha-102, and 0.082 for Sakha-104. The lower significance value is 0.200 for the three rice varieties (Table 1). The Shapiro–Wilk test results show that SW statistics is 0.972 for Giza-178, 0.966 for Sakha-102, and 0.980 for Sakha-104 with significance values as 0.473 for Giza-178, 0.611 for Sakha-102, and 0.758 for Sakha-104. The normality tests results and Q–Q plots (Fig. 2) give a good indicator that the LAI data distribution for the three rice varieties are more likely to follow a Gaussian distribution hence most of LAI data fall almost perfectly along the normality line and that normal distribution of data is not obtained by chance.

4.4. Homogeneity of variance

The results of all variants of Levene's test (Table 2) show that the obtained differences in sample variances are unlikely to have occurred based on random sampling. Thus, the null hypothesis of equal variances is rejected and it is concluded that there is a significant difference between the variances in

Table 1 Normality test for LAI data.

Rice variety	Kolmogorov–Smirnov (KS)			Shapiro–Wilk (SW)		
	KSs.	df	Sig.	SWs.	df	Sig.
Giza-178	.073	35	.200	.972	35	.473
Sakha-102	.129	21	.200	.966	21	.611
Sakha-104	.082	35	.200	.980	35	.758

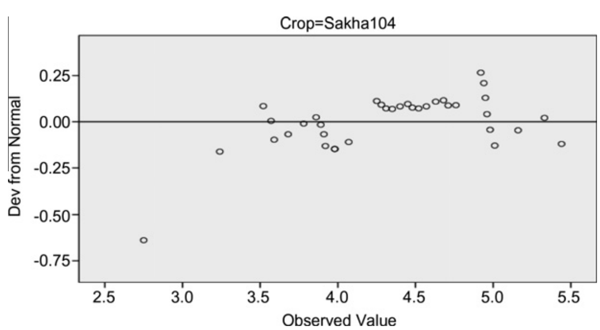

Figure 2 Detrended normal Q–Q plot for LAI data (Sakha-104).

the population. Also, the results spread versus level plot indicate that the variance is not equal between LAI data samples.

4.5. Analysis of variance

An important first step in the analysis of variance is establishing the validity of assumptions. One assumption of ANOVA is that the variances of the groups are equivalent. As mentioned before, the Levene's test has already established that the variances across groups are significantly different, though the assumption of equal variances is violated. The F statistics is robust to unequal variances when sample sizes are equal or nearly equal. However, when both the variances and the sample sizes differ, the standard F statistics lacks power and is prone to give incorrect results. Although, ANOVA is robust to unequal variances with groups of near equal size; however, there are an unequal number of observations per group. In this case, to obtain robust F statistics, one-way ANOVA with linear trend test combined with Welch and Brown–Forsythe tests for the equality of group means were performed.

The results of ANOVA test (Table 3) tend to reject the null hypothesis and accept that the differences of means between groups (mean square = 4.412) are real significant differences than to be observed between groups. The Welch and Brown–Forsythe statistics, which are more powerful than the standard F statistics when samples sizes and variances are unequal, also proves this result with significance. Linearity results also tend to reject the alternative hypothesis and accept that there is a linear trend (sig. = 0.918) between groups means with slope of 0.398.

Regression analyses were performed to examine the relationship between LAI and NDVI in the three rice varieties. For the purpose of testing hypotheses about the values of model parameters, an Ordinary Least Square Regression Model (OLSRM) was performed between LAI and NDVI for the three rice varieties. The results indicated that the error term has a normal distribution with a mean of 0 and independent of the variables in the model for the three varieties. However, the variance of the residuals for the three varieties is not constant across the values of the predicted values.

This heteroscedasticity of the error term violates the assumptions of the Ordinary Least Square Regression Model (OLSRM). The model no longer provides optimal model estimates, so there is a need to correct the heteroscedasticity in the residuals by using a Weighted Least Square Regression Model (WLSRM) model in order to obtain valid estimates in further

Table 2 Levene's test results for homogeneity of variance.

		Levene statistics	df1	df2	Sig.
LAI	Based on mean	3.195	2	91	.046
	Based on median	3.203	2	91	.045
	Based on median and with adjusted df	3.203	2	80	.046
	Based on trimmed mean	3.185	2	91	.046

df = degree of freedom, Sig. = significance value.

Table 3 ANOVA combined with linear trend.

		Sum of squares	df	Mean square	F-test (ANOVA)	Sig.
Between groups	(Combined)	8.824	2	4.412	10.975	.000
	Linearity	8.820	1	8.820	21.939	.000
	Deviation from linearity	.004	1	.004	.011	.918
Within groups		94.584	91	.402		
Total		45.408	93			

Table 4 WLSR model coefficients for rice varieties.

Model	Coefficients (a, b)					
	Giza-178		Sakha-102		Sakha-104	
	B	Std. error	B	Std. error	B	Std. error
Constant	0.130	0.38	8.913	0.91	0.281	1.16
NDVI	11.388	1.35	−13.207	2.86	11.114	3.33
%		82		72		50

analyses. The regression model is affected by high leverage and high influence points. The high leverage points give its extra weight in the computation of the regression and the high influence points affect the slope of the regression. To deal with these points, a weighting variable was defined. Using the weighting variable gives high influence points resulting in more precise regression estimates. A range of weight transformations were tested and a range of power values were tried for a more tuned model. For each of the power values, a weighted least squares model was fitted and the value that gave the best fit (largest log-likelihood) was selected.

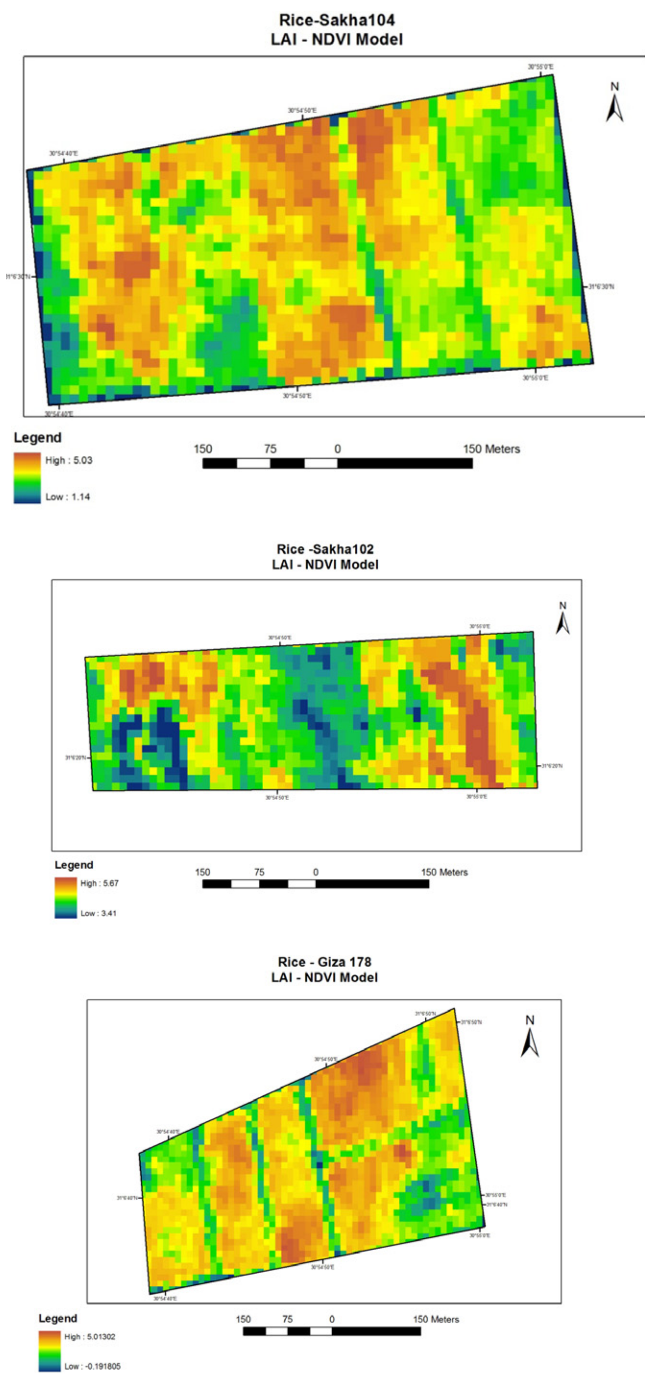

Figure 3 LAI maps for the three rice varieties.

The results of the Weighted Least Square Regression Model (WLSRM) for the three rice varieties (Table 4) indicated that, the fraction of the variability that is fitted by the model is 82% for Giza-178, 72% for Sakha-102, and 50% for Sakha-104 of the total LAI variability. According to the observed significance levels for the t statistics, the independent variable of the regression model has statistically significant predictive capability for the three rice varieties. F test for the regression models indicated that the correlation was high in the case of Giza-178 and Sakha-102 and moderate with the case of Sakha-104.

The highest accuracy (r = 0.82) was produced with LAI–NDVI model for Giza-178 variety. The generated models were applied on SPOT4 data to generate LAI map and to have LAI value for every pixel in the study area. Fig. 3 shows LAI map for rice variety Sakha-104.

5. Conclusion

The study was carried out to generate inversion NDVI–LAI models for three widely used rice varieties in Egypt during two rice growing seasons in 2008 and 2009. Three statistical models for the three varieties were generated with adequate accuracy. The main inputs for the generated models were LAI field measurements that were collected through LAI-Plant Canopy Analyzer device and NDVI values that were collected from SPOT4 data. The generated models are statistical empirical models that are limited to the area and the surrounding environment. The main dataset for the modeling process were chosen under the optimal production conditions of Sakha experimental field in Kafr El-Sheikh governorate and modifications could be necessary when applying these models in different geographical locations under different conditions. The generated models could be displayed in GIS environment to produce LAI maps. These maps can be used by the extrapolation approach to assess the rice area cultivation in Egypt as well as rice yield prediction.

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